

AN INVERSE MONTE-CARLO BASED METHOD TO ESTIMATE PRE-CRASH DISTRIBUTION FOR VRU SAFETY

Hariharan, Sankara Subramanian

Sudipto, Mukherjee

Anoop, Chawla

Indian Institute of Technology Delhi
India

Dietmar, Goehlich

Technical Universitaet Berlin
Germany

Paper Number 15-0421

ABSTRACT

Current safety standards are based on maximum stiffness measures over a grid on the frontal surface of a vehicle. The safety of VRU is also influenced by the overall shape of the impacting vehicle. “Initial conditions” [IC] from the dominant crash scenarios are used for CAE simulations in Industrial practice to tweak designs. The IC’s to design for are decided based on cluster analysis from reconstructions of crash data. Currently, CAE methods to predict the outcomes (final resting state of interacting elements) of a crash deterministically, given the initial conditions are available. But there are no established methods to do the inverse process, that is ascertain the conditions at the initiation of the crash given the final static state of the interacting elements. Recorded data being the final resting state of the interacting elements, the inverse problem is of significance, and is usually tackled by heuristics and iterations augmenting physical laws. While reconstructions of specific cases require detailed observation and experienced personnel, it is hypothesized that estimating a distribution of the pre-impact measures in crashes is more robust with respect to a distribution of the post impact observation than that of individual crashes.

Individual cases from crash reconstruction, approximated to a Gaussian “normal” probability density function, were assumed for the probability of occurrence of individual cases. Crash physics was captured using a multibody simulation in MADYMO solver. An inverse Monte Carlo [MC] simulation with MADYMO solver as the system under study was modelled in “FME” module in statistical software “R”.

A set of post-crash data on head hit location [O1] was generated using forward MC simulation. The variable parameters were four different vehicle profiles, relative position of 50M along vehicle lateral axis [I2] and the relative orientation of with respect to vehicle. The pedestrian represented using one 50th percentile male [50M] pedestrian model was not varied.

Starting with the distribution of “O1” and an “I2” distribution perturbed by up to 20% in mean value as input, an I2 was computed using inverse MC. The “I2” distribution from inverse MC showed less than 10% deviation from the original v3 data set mean with randomized values of untracked variables.

During the inverse MC process, the quality of “fit” to a desired O1 distribution was tracked using the sum of root mean square of differences between normalized density coefficients and a “relaxation parameter” computed as squared logarithmic probability to a normal distribution. The stabilization of the tracking parameter indicated a robust solution.

INTRODUCTION

Vulnerable Road Users (VRU) is a term used to collectively refer to pedestrians, bicyclists and motorcyclists. Report by WHO (World Health Organisation 2013) shows bicyclists and pedestrians to constitute over a quarter (27%) of the total traffic related fatalities in the world. VRU safety in crash scenarios involving cars has remained an active area of research with safety tests put in place for pedestrian safety using body-form impact on the vehicle front to estimate the potential injury risk. One of the components of VRU – pedestrians - represent a majority of VRU exposed to traffic threats. Data from (World Health Organisation 2013) also indicate pedestrian fatalities to be 22% of total road fatalities. Pedestrian safety has been addressed by regulatory and rating tests like Euro-NCAP

(Hobbs and Mcdonough 1998) and by indirect indicators for threats to pedestrians from car fronts. These rating and regulatory tests have been modelled for estimating threats to target human populations and crash scenarios selected based on data in crash databases. Current safety standards are based on maximum stiffness measures over a grid on the frontal surface of a vehicle. It is however well understood that safety of VRU is also influenced by the overall shape of the impacting vehicle (Crandall et al. 2002).

Advancement in CAE has led to crash simulations being used as a method for virtually replicating crashes. In industrial practice, CAE simulations are used to model using “initial conditions” [IC] from the dominant crash scenario to tweak designs. The IC’s to design for are decided based on cluster analysis from reconstructions of crash data. Lack of clear data from post-crash scenes limit the efficiency of replications of crashes through computer simulations. Crash reconstructions of specific cases require detailed observations of the crash scene and experienced personnel to apply heuristics and iterate on simulations. It is hypothesized that estimating a distribution of the pre-impact measures in crashes is more robust with respect to a distribution of the post impact observation than inferring the IC’s of individual crashes through reconstructions. We also note that for design or standard setting purposes, it is the statistics as opposed to specific cases which is of relevance. The authors (S subramanian et al. 2014) have proposed a method based on inverse Monte Carlo to estimate pre-crash variables using limited post-crash data. This work evaluates the robustness of the inverse Monte Carlo method using a synthetic randomized post-crash data to estimate pre-crash data.

METHODOLOGY

Crash simulation using computational techniques work on uni-directional physics of crash. The post-crash effects can be estimated using known pre-crash conditions. This work will discuss verification of previously proposed methodology to estimate pre-crash variables to model crash simulations. The first step of this study was to generate synthetically randomized crash data equivalent. Vehicle velocity (I1), vehicle category denoted by vehicle profile (I2), location of pedestrian in lateral plane of vehicle (I3) and orientation of pedestrian with respect to vehicle with pedestrian hit on left or right (I4) were selected for variation. The output of the crash simulation (O1) was captured. The present objective was to estimate most likely lateral position of pedestrian in front of vehicle (I3). An inverse Monte Carlo based on ‘Mu’ measure was executed with O1 distribution to estimate variable I3.

Crash simulation

Vehicle to pedestrian crash was simulated using multibody MADYMO solver with pedestrian represented by 50th percentile male pedestrian model. Vehicle was represented using multibody model for vehicle front and the crash scenario was similar to previous work by authors (S subramanian et al. 2014).

Generation of synthetic crash data

A synthetic randomized crash data was generated using forward Monte Carlo (FMC) simulation using sensitivity study module of OptiSlang (Dynardo GmbH 2011) with 500 samples. The input variables I1 to I4 were classified as discrete and continuous variables with ranges of values shown in Table 1. I1 and I4 were discrete variables with three and four levels of values respectively. I2 and I3 were varied continuously in the range indicated. The input variable I2 was initialized with two values for every set of I1, I3 and I4. Two values of I2 was generated to simulate a “left” and “right” side impact of pedestrian with all other variables in same level for one iteration.

Table1.
Input variables to Monte Carlo simulations

	Unit	Variable Type	Range
Velocity (I1)	m/s	Discrete	30,40,50
Angle (I2)	Degrees	Continuous	-30 to +30
Location (I3)	m	Continuous	0.2 to 1.8
Category (I4)	No unit	Discrete	A, B, D or generic

The FMC study had an objective of data distribution generation of the head hit location of pedestrian (O1). An overview of the process is shown in Figure 1. The variables I1 to I4 form the input to vehicle-pedestrian crash

simulation in MADYMO. MADYMO solver output files were read back by OptiSlang for the estimated primary head hit point on the vehicle by tracking the head and vehicle front positions through the simulation.

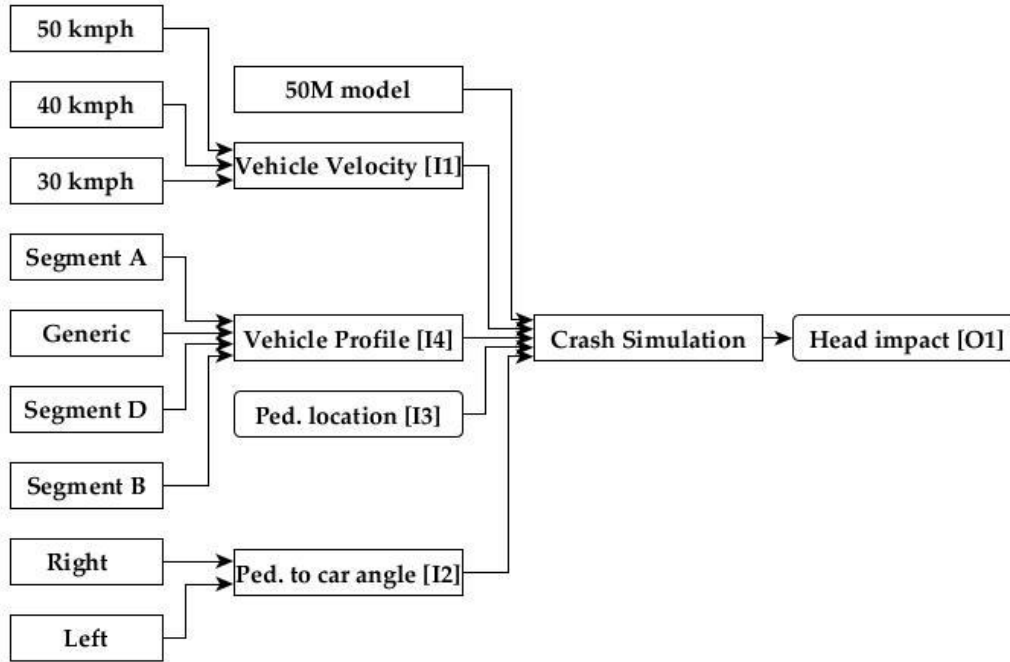


Figure1. Methodology for a synthetic data generation using Monte Carlo forward method

The data generated during FMC study of the I3 and O1 were exported from OptiSlang and a normal distribution was “fitted” to the data using modules in open source software R. The estimates of O1 distribution mean and variance obtained by the end of FMC would be used to provide an “expected” distribution of O1 for Inverse Monte Carlo method to estimate for I3 distribution. A normal distribution fitted to O1 had a mean of

Estimation of a pre-crash variable

Inverse Monte Carlo (IMC) based simulation was setup using FME module(Soetaert and Petzoldt 2010) in R language. The system under study was MADYMO solver with output being processed to provide O1 values. Most of the fine-tuning variables of FME were in default values. The number of iterations of this sample study was restricted to 500 iterations.

A ‘ μ ’ [Mu] measure was formulated based on the suggestions in FME documentations. μ was sum of RMS difference in density coefficients of present IMC iteration O1 values and similar values output from FMC along with a logarithmic normal probability of the I2 on expected normal probability function. The application μ in this work is shown in equation (1). A detailed discussion of μ can be found in (S subramanian et al. 2014).

Sample calculation of μ

$$\mu = CF \cdot RMS \cdot 100 + RP \quad (1)$$

Where,

RMS - Root mean square difference in density coefficients between FMC and IMC

CF – Correction Factor

RP – Relaxation Parameter = $-2 \cdot \log(\text{Normal Probability})$

For a specific I2 value of 145cm, the Normal distribution for RP has mean of 100cm and standard deviation of 45cm.

The normal probability of I2 = $4.9e-5$

$2 * \log(\text{Normal probability}) = \text{RP} = -8.6137$

RMS calculated between FMC and IMC values of I2 were 0.015. The RMS values are multiplied by a factor of 100 in this case to make them significant in comparison to the RP.

$\mu = 0.015 * 100 - 8.6137 = 10.19$

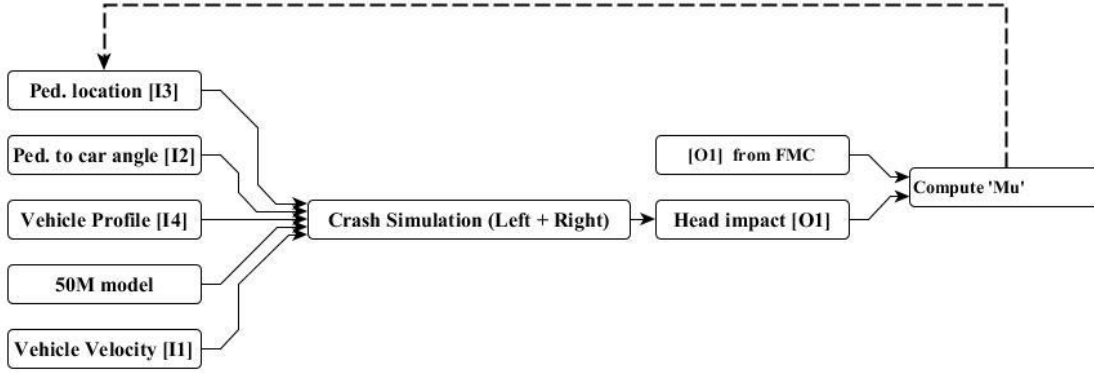


Figure2. Methodology to estimate pre-crash variable using inverse Monte Carlo method

RESULTS AND DISCUSSION

Variation of μ

The parameter ' μ ' is expressed as a sum of $\text{CF} * \text{RMS}$ and RP. During IMC simulations, the best possible solution can be obtained when the value of ' μ ' reduces to minimum. The variation of RMS is indicative of global variation of O1 from IMC with corresponding value from FMC. The variation in RMS is shown in Figure 3, which indicate the value to stabilize over 300 iterations.

The value of RP was controlled by the new data point generated by randomized number generator of Monte Carlo process. The variation of RP and μ (Mu) is shown in Figure 4. The variation of RP between 15 and 20 is the direct result of normal probability calculation. The influencing part, μ , was the global parameter $\text{CF} * \text{RMS}$ which stabilized by 300 iterations and was relatively stable beyond that point. It was concluded that iterations beyond 600 may not be necessary.

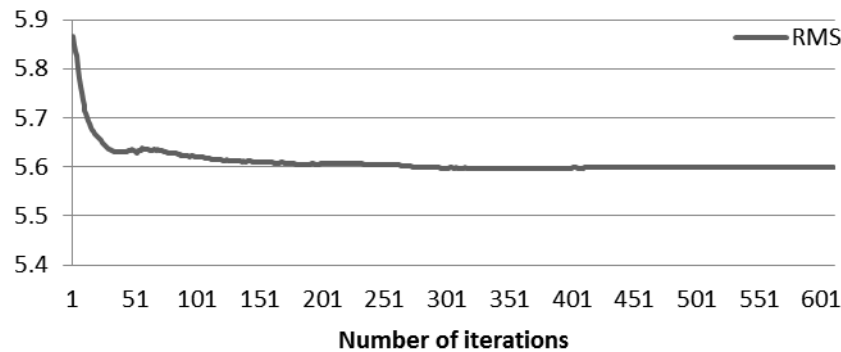


Figure3. Variation of RMS in IMC

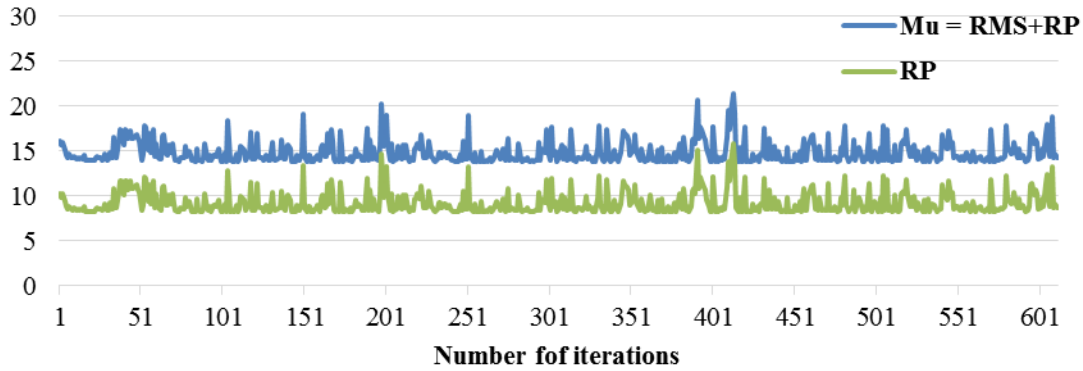


Figure4. Variation of ‘ μ ’ in IMC

Variation of O1

The objective of IMC simulation was to estimate the I2 distribution based on output distribution O1 processed from FMC simulations. In this study, a Gaussian normal probability function was assumed for all variables. Every head hit location (O1) was recorded and their density coefficient was obtained. The O1 density distribution obtained from FMC indicated a non-normal behavior as shown as dark shaded bars in Figure 5. The O1 distribution obtained from IMC process is indicated using lighter shades of bars in Figure 5, which show a mixed match with O1 from FMC. The O1 obtained from IMC process was generated with influence of normal probability which is evident with a peak near the middle of the O1 graph of density coefficients. The variation of the density coefficients of O1 distribution of FMC and IMC showed a Pearson coefficient of 0.83.

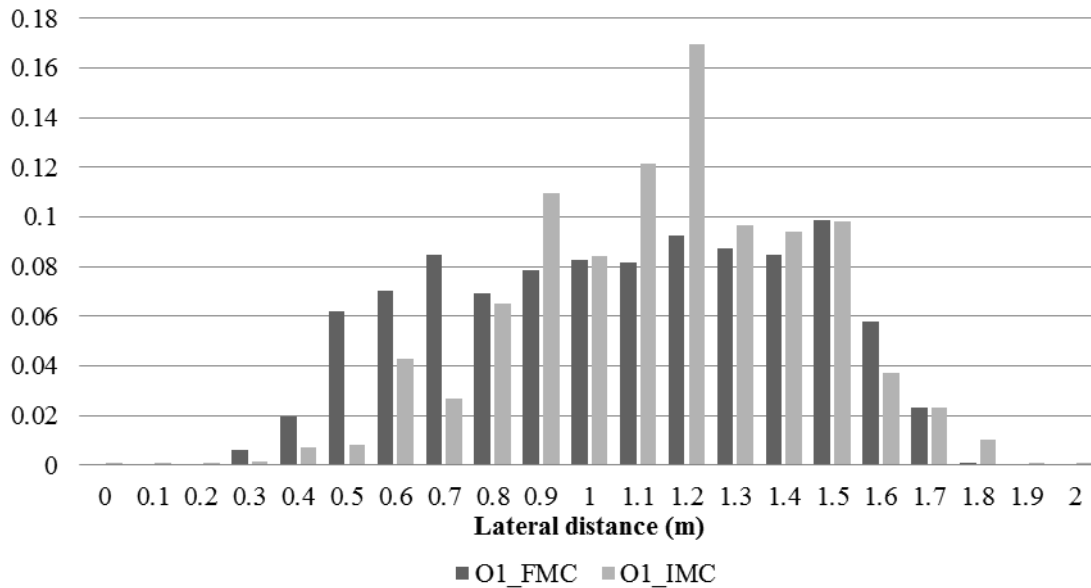


Figure5. Comparison density coefficients of O1 from FMC and IMC

The I2 variable was fitted to normal distributions by similar methods as O1 and their mean and variances were compared. Table 2 shows variable I2's normally distributed mean and standard deviation from FMC and IMC processes. Mean of I2 from IMC varies under 10% from the mean of I2 from FMC. The assumed normal distribution for comparison of I2 had mean at 1.10m and standard distribution of 0.25m. The initial value of I2 in IMC was assumed to be 1.45m. There was a significant shift in overall distribution towards FMC values.

Table2.
Comparison of I2 from FMC and IMC

	FMC	IMC
Mean I2 (m)	1.01	1.08
Variance I2 (m)	0.34	0.24

Limitations

A Gaussian normal distribution was assumed for all variables to estimate the probability. With clearer data available on specific variables, a better prediction probability function can be incorporated. The μ measure remains sensitive to the units of length used and appropriate correction factors need to be updated for better convergence. Sample runs of higher than 500 were not studied as the simulations trend was visible with shift in mean towards expected values.

The comparison was based on kinematic distributions, both at the input and output. The point of real concern is predicting trauma levels. An increased performance, when extended to HBM's applications (with significantly enhanced degrees of freedom) in conjunction with injury models has to be attempted.

CONCLUSIONS

During the inverse MC process, the quality of “fit” to a desired O1 distribution was tracked using the sum of root mean square of differences between normalized density coefficients and a “relaxation parameter” computed as squared logarithmic probability to a normal distribution. The stabilization of the tracking parameter indicated an optimal solution.

This methodology combined with advanced tools like FE human body model will improve injury prediction efficiency of CAE tools.

REFERENCES

- [1] Crandall, J.R. et al. 2002. Designing road vehicles for pedestrian protection. *BMJ* (324), pp. 1145–1148.
- [2] Dynardo Gmbh 2011. *Dynardo Gmbh OPTISLANG - The optimizing structural language v3.2.1*. Weimar, Luthergasse 1 D, Germany: Dynardo Gmbh.
- [3] Hobbs, C.A. and McDonough, P.J. 1998. Development of the European New Car Assessment Programme (Euro NCAP). In: *ESV 98-S11-O-06*.
- [4] S subramanian, H. et al. 2014. Methodology for estimation of probable location of VRU before impact using data from post-crash analysis. In: *IRCOBI conference 2014*.
- [5] Soetaert, K. and Petzoldt, T. 2010. Inverse Modelling , Sensitivity and Monte Carlo Analysis in R Using Package FME. *Journal of statistical software* 33(3), pp. 1–28.
- [6] World Health Organisation 2013. *Global status report on road safety 2013: supporting a decade of action*.